

## Super Cycles in Real Metals Prices?

JOHN T. CUDDINGTON and DANIEL JERRETT\*

*To borrow a phrase once used about business cycles, it can be said that “the study of super cycles necessarily begins with the measurement of super cycles” (adapted from Baxter and King, 1999). Are metal prices currently in the early phase of such a “super cycle”? Many market observers believe the answer is yes. Academics, on the other hand, are generally skeptical about the presence of long cycles. This paper searches for evidence of super cycles in metal prices by using band-pass filters to extract particular cyclical components from time series data. The evidence is consistent with the hypothesis that there have been three super cycles in the past 150 years or so, and that we are currently in the early phase of a fourth super cycle. Most analysts attribute the latter primarily to Chinese urbanization and industrialization. [JEL E3, Q0]*

*IMF Staff Papers* (2008) **55**, 541–565. doi:10.1057/imfsp.2008.19;

published online 19 August 2008

Many market observers believe that metal prices currently in the early phase of a “super cycle” driven by the industrialization and urbanization of the Chinese economy, and perhaps other economies as well. Alan Heap of Citigroup, for example, declared in March 2005 that “a super cycle is underway, driven by material intensive economic growth in China” (Heap, 2005, p. 1).<sup>1</sup>

---

\*John T. Cuddington is the Coulter Professor of Mineral Economics and Daniel Jerrett is a Ph.D. candidate at the Colorado School of Mines. Helpful discussions with Neil Brewster, Graham Davis, Rod Eggert, Alan Heap, and John Tilton are gratefully acknowledged.

<sup>1</sup>See also Armstrong, Chaundry, and Streifel (2006), Heap (2007), and Morgan Stanley (2006), as well as Rogers (2004), who cofounded the Quantum Fund with George Soros, and

Just what are super cycles and what are their underlying causes? It is clear from the writings of super-cycle proponents that these cycles are “super” in two senses. First, they are long-period cycles with upswings of roughly 10 to 35 years, implying complete cycles of, say, 20 to 70 years. Second, they are broad-based, affecting a range of industrial commodities, including metals and other nonrenewable resources. Heap (2005, pp. 1–2), defines a super-cycle expansion as a “prolonged (decades) long-trend rise in real commodity prices, driven by urbanization and industrialization of a major economy.” He believes there have been two earlier super-cycle expansions in the past century and a half. The first ran from the late 1800s through the early 1900s, driven by economic growth in the United States. The second was from roughly 1945 through 1975, initiated by post-war reconstruction in Europe and fueled by Japanese post-war economic expansion.

Heap also argues that super cycles are demand driven. This implies super-cycle components in individual commodity prices should be strongly positively correlated. That is, they should exhibit strong co-movement, perhaps with some phase shifting as developments in particular commodities might lead or lag upswings in other commodities.

This paper takes an agnostic view on the presence of super cycles, let alone their underlying causes. We argue in the spirit of Baxter and King (1999, p. 575) that for mineral and financial economists “the study of [super] cycles necessarily begins with the measurement of [super] cycles.”<sup>2</sup> Thus, the primary objective here is to document super-cycle facts using recently developed band-pass (BP) filters and roughly a century and a half of annual price data for the six base metals currently traded on the London Metal Exchange (LME)—aluminum, copper, lead, nickel, tin, and zinc.<sup>3</sup> Using these data, this paper (1) documents the existence, frequency, and amplitude of super cycles in metal prices; (2) investigates whether super-cycle timing is consistent with that discussed by super-cycle proponents; and (3) examines the extent of co-movement among the super cycles in the LME6 metal prices.<sup>4</sup>

As the end use summary statistics from the London Metal Exchange (2008) shown in Table A1 confirm, the six LME metals are all critical inputs in residential and commercial construction activity, transportation and other infrastructure investments, and/or heavy manufacturing. These metals are often used in sectors that are expanding in tandem. Moreover,

---

was among the first to highlight commodities as a long-term investment opportunity in the new millennium. Others in the investment industry followed.

<sup>2</sup>This is an adaptation of the comment that Baxter and King (1999) made about business (rather than super) cycles.

<sup>3</sup>Although producer price series from industry sources span many decades, LME trading began at different times for the various metals: copper and tin (1877), lead (1903), zinc (1915), aluminum (1978), nickel (1979).

<sup>4</sup>For an examination of super cycles in steel, pig iron, and molybdenum, see Jerrett and Cuddington (2008).

they are joint inputs in many construction (buildings, homes, and factories) and manufacturing applications (automobiles, freight cars, ships, and airplanes). On the supply side, base metals are often joint outputs from individual mining operations. Thus, there are strong economic linkages—supply and demand-side—to explain why co-movement of the metals prices may be present.

The econometric approach employed here uses BP filters developed by Baxter and King (1999) and Christiano and Fitzgerald (2003) to search for evidence of super cycles. First, a review of the writings of super-cycle proponents is undertaken to decide which periodicities constitute super cycles. Second, an appropriate BP filter is applied to long-span metal price series to extract their super-cycle components. Third, super-cycle components for the six metals are examined using correlation and principal component analysis to determine whether evidence on the timing and concordance of these cycles supports the super-cycle hypothesis.

Our findings are consistent with the hypotheses that (1) there have been three metal price super cycles in the past 150 years or so and (2) world metal markets are currently in the early stages of a fourth super cycle. The dating of the super cycles broadly matches the timing suggested by earlier analysts using less formal approaches. Moreover, our correlation and principal component analyses suggest that the super cycles in the six metal prices are highly correlated. This evidence is consistent with the claim that super cycles are caused by prolonged demand expansions, as major economies move through the rapid industrialization and urbanization phases of their economic development processes.

### I. Motivation and Background

There have been numerous studies of trends and cycles in commodity prices, ranging from informal graphical inspection of the data, combined with a good knowledge of economic history and the peculiarities of the metals markets being studied, to rigorous statistical decomposition techniques. Good examples of the former approach include Maxwell (1999); Heap (2005) and (2007); Radetzki (2006); and Tilton (2006). Examples of times series econometrics approaches include Cuddington and Urzúa (1989); Deaton and Miller (1995); Cashin and McDermott (2002); Cuddington, Ludema, and Jayasuriya (2007); and Gilbert (2007). A number of authors have analyzed the movement of metal prices over the business cycle as well as co-movements among commodity prices (see Labys, Achouch, and Terraza, 1999; McDermott, Cashin, and Scott, 1999; and Pindyck and Rotemberg, 1990). Lower frequency cycles in metals prices, in contrast, have received scant attention.

Who cares about possible super cycles in metals prices? Although academic economists have a longstanding interest in studying trends and cycles, especially at business cycle frequencies, they are generally very skeptical about the presence of long cycles, such as Kuznets or Kondratiev

cycles. Many have argued that “it amounts to seeing patterns in a mass of statistics that aren’t really there.”<sup>5</sup> Kuznets cycles, for example, have been critiqued by Adelman (1965); Howrey (1968); and, more recently, Cogley and Nason (1995). Nelson and Kang (1981) highlight the “spurious periodicity” that can be introduced by inappropriate de-trending techniques, arguing that long cycles may be a statistical artifact.

In spite of this longstanding skepticism of long cycles, there have been a number of recent efforts by distinguished economists to study them. See Blanchard (1997); Solow (2000); Comin and Gertler (2006); and Evans, Honkapohja, and Romer (1998), all of whom theorize about and/or empirically search for growth cycles in macroeconomic data. Comin and Gertler (2006), for example, use BP techniques similar to those used here to extract medium term cycles—which they define as cycles with periods of up to 50 years—from common macroeconomic series. They then go on to develop a real business cycle model to explain these medium-term cycles, as well as their interaction with conventional business cycles (with periods between two and eight years).

The study of super cycles in metals prices is important for numerous industries and governments. The investment community is touting the virtues of “commodities as an asset class” that can produce large diversification gains when added to portfolios with stocks and bonds—much the way international investments were promoted 10 to 20 years earlier (see Gorton and Rouwenhorst, 2004). The number of commodity-based mutual funds, hedge funds and exchange-traded funds has grown rapidly in response to investor appetite for such investments. M&A activity in the mining sector has proceeded at a torrid pace in the last several years.

Mining industry capital investments have long gestation periods, so the prospects of an emerging metals super cycle has important implications for profitable capacity expansion by both private and government-owned mining companies.<sup>6</sup> Regarding the long gestation periods for mining investments, the observations of Davis and Samis (2006, p. 274) are interesting: “[E]xploration investment is unlike most other investment activities due to the long time frame between the expenditure of capital and the realization of revenues. An analysis of 54 major base- and precious-metal deposits around the Pacific rim by Sillitoe (1995) reveals that the time from initial exploration spending to the discovery drill hole averaged 14 years for base metal deposits and 22 years for gold deposits. There is then an average of a further 13.5 years to first production for base metal deposits and seven years to first production for gold deposits. That is, where exploration is successful there is an average of 27.5 years from initial spending to cash flow generation for base metal deposits. The average at gold deposits is 29 years.” Of course, some mining

---

<sup>5</sup>See [en.wikipedia.org/wiki/Kondratiev\\_wave](http://en.wikipedia.org/wiki/Kondratiev_wave).

<sup>6</sup>See Radetzki (2008, Chapter 9) on the importance of the latter in the mineral and energy sectors.

investments will come on stream faster, to the extent that they expand existing operations or undertake “green field” exploitation of known, but as yet undeveloped, mineral reserves.

Many governments rely heavily on resource revenues either from their direct ownership of resource extraction companies or the tax revenues and royalties obtained from private firms operating within their borders. Therefore understanding super cycles is of great importance to metal exporting countries whose fiscal revenues have been surging in recent years. Commodity export booms have not always been well managed by exporting countries in the past.

It is conventional wisdom in the metals industry that short-run price elasticities of demand and supply are both low, with the latter reflecting short-run capacity constraints in the mining and processing (smelting, refining, and treatment) sectors. The long-run price elasticity of supply, on the other hand, is thought to be much higher. For example, Tilton and Lagos (2007) argue that “the long-run supply curve for most metals rises at first (reflecting the dwindling number of exceptional deposits with unusually low costs), but then levels off and becomes relatively flat...if the relatively flat portion of the supply curve covers the relevant range of future global demand, which seems likely, whether it is nearly or completely horizontal matters little. In either case, demand has little influence on long-run prices.” Note that with this view regarding long-run supply responses, metals prices should *not* exhibit super cycles if the metals industry moves to the “long run” reasonably quickly. (Alternatively, one might argue that super-cycle demand expansions temporarily drive up factor input costs in the mining sector. This temporarily shifts the (relatively flat) long-run supply curve upward during super cycles, and down thereafter.)

So how long does it take to get to the long run? In order for prolonged demand expansion to have a super-cycle effect on prices—where they are above their long-run trend for 10 to 35 years—one must argue that capacity constraints and/or the sharp run up in mining input costs (super truck tires, energy inputs, mining engineer services, permitting costs, etc.) prevail for a decade or more. Alternatively, if bulk shipping and port facilities are stretched to the limit, as they have been in recent years, sharp rises in transportation costs could also put sustained upper pressure on metals prices until shipping and port capacity constraints are alleviated.

World Bank and Wall Street analysts both conjecture that supply responses in the current super cycle will be much different than in prior cycles. Underinvestment in the mining sector over the past decade, due to sustained low metals prices implies that there are very few large capacity-enhancing projects in the pipeline. The result will be longer periods to bring new capacity online. Environmental permitting and sustainability issues are adding to this lag time. In addition, declining ore grade is necessitating a return to deep underground mining, with the concomitant loss of scale economies from open-pit mines. Currently, the lack of skilled labor is also an acute problem for the mining sector. Contract negotiations

have led to strikes in various countries, as mine workers have fought for their “fair share” of the windfall profits resulting from surging metals prices.

Clearly, it would be desirable to have a “slick structural model,” as one commentator observed, to explain the underlying causes of super cycles and their likely persistence for individual metals, not to mention co-movement among them. We hope that the documentation of super-cycle facts in this paper will lead to the development of such models.

## II. Super Cycles and the BP Filter

This paper applies recent statistical decomposition or filtering methods to the problem of identifying super cycles. Using this BP filter approach, economic time series can be represented as a combination of cyclical components of various periodicities or frequencies. As Christiano and Fitzgerald (2003, p. 1) argue:

The theory of the spectral analysis of time series provides a rigorous foundation for the notion that there are different frequency components of the data. An advantage of this theory, relative to other perspectives on decomposing time series, is that it does not require a commitment to any particular statistical model of the data. Instead it relies on the Spectral Representation Theorem, according to which any time series within a broad class can be decomposed into different frequency components. The theory also supplies a tool for extracting those components. That tool is the ideal band pass filter.

Unlike univariate models that assume deterministic or stochastic trends that are constant over time (with the possible exception of detected break points), the trend-cycle decomposition or filtering methods used in this paper allow for *gradual* change in long-term trends, as well as cycles of different frequencies or periodicities.<sup>7</sup> Filtering techniques to isolate particular frequencies in an economic time series have been primarily developed in the context of business cycle research in macroeconomics. The Hodrick-Prescott (HP) filter is the most popular, but more flexible alternatives are now available. Baxter and King (1999) argue that it is difficult to know how to choose the smoothness parameter  $\lambda$  in the HP filter when studying cycles of different periodicities. As an alternative, they develop and recommend the use of BP filters. These filters are designed to extract stochastic cyclical components with a specified range of periodicities from individual time series.<sup>8</sup> For example, Baxter and King show that if a BP(6, 32) filter is applied to a series  $Y$  of quarterly data, the

---

<sup>7</sup>Recall that periodicity and frequency in a cycle are inversely related. The period of the cycle is its duration from one trough, through the expansion and contraction phase, to the beginning of the next trough. The frequency is the number of cycles per unit of time (in days, month, years, etc., depending on the frequency with which the data are measured).

<sup>8</sup>These techniques attempt to isolate stochastic rather than *deterministic* cycles in the data; they do not amount to fitting the best possible regular sine wave to the data series.

result is a stationary series with cyclical components with periods between 6 and 32 quarters. This would imply upward expansion phases of one-half these amounts—3 to 16 quarters—if the upswings and downturns are of equal duration (which they need not be). Baxter and King (1999) argue convincingly that when applied to quarterly data, the BP(6, 32) filter yields a filtered series isolating primarily business-cycle frequency fluctuations. Both lower frequency cycles (and trends) and higher frequency components (for example, seasonality and noise) are filtered out. Only fluctuations within the band of 6 to 32 quarters are retained when an “ideal” filter is applied.

The “ideal” BP filter, which isolates *only* specified frequencies, uses an infinite number of leads and lags when calculating the filter weights from the underlying spectral theory. Of course, a finite number of leads and lags must be used in practice; so a truncation decision must be made. Using a larger number of leads and lags allows for more precise results, but renders unusable more observations at the beginning and the end of the sample. Baxter and King stress that a filter must be symmetric in terms of the number of leads and lags to avoid causing phase shift in the cycles in filtered series. Baxter and King and Christiano and Fitzgerald (2003) develop alternative finite sample approximations to the ideal symmetric filter. Christiano and Fitzgerald also derive *asymmetric* filters, which have the advantage that they allow us to compute cyclical components for all observations at the beginning and end of the data span. The cost, as Christiano and Fitzgerald show, is very minor phase shifting, at least in their applications.

Although Christiano and Fitzgerald (like HP and Baxter and King) are interested in business-cycle analysis, they also provide a couple of interesting macroeconomic applications of their symmetric and asymmetric filters for extracting lower frequency components of economic time series. The first involves an analysis of the Phillips curve relationship between unemployment and inflation in the short run vs. the long run (that is, the high- vs. low-frequency components). The second application examines the correlations between the low-frequency components of monetary growth and inflation. Our paper is the first to apply the BP filters to natural resource issues, including metal markets.

BP filters are well suited for our objective of attempting to measure super cycles in metals prices. One can define the range of cyclical periodicities that constitute “super cycles,” and then use the BP filter to extract those cyclical components. Given current interest in whether a new super cycle is emerging in the final years of our data sample, the asymmetric Christiano and Fitzgerald BP filter (ACF) is especially useful because it allows one to calculate super-cycle components at the end of our data sample.

We employ the ACF BP filters to decompose the natural logarithms of real metal prices into three components: the long-term trend ( $LP\_T$ ), the super-cycle component ( $LP\_SC$ ), and other shorter cyclical components

( $LP\_O$ ).<sup>9</sup> By construction, these three components sum to the price series itself:

$$LP_t \equiv LP\_T_t + LP\_SC_t + LP\_O_t.$$

One must first decide what cycle periods encompass super cycles. Heap's (2005, 2007) discussion implies that super cycles have *upswings* that last from 10 to 35 years, implying that the period of super cycles is roughly twice that amount.<sup>10</sup> Thus, we apply the  $BP(20, 70)$  filter to each price series to extract its super-cycle component:

$$LP\_SC \equiv LP\_BP(20, 70).$$

With this definition of the super cycle, it is natural to define the *long-run trend* as all cyclical components with periods in excess of 70 years:

$$LP\_T \equiv LP\_BP(70, \infty).$$

As mentioned above, this approach does not assume the trend is constant over the entire 150 years span of our data set. Rather the trend can evolve slowly over time.

Having identified the long-term trend and the super cycle, what remains are the shorter cyclical components, which therefore include cycles with periods from 2 (the minimum measurable period) through 20 years:

$$LP\_O \equiv LP\_BP(2, 20).$$

It will be convenient in the graphical analysis below to examine the “nontrend” component of prices  $LP\_BP(2, 70)$ , which is the total deviation from the long-term trend.<sup>11</sup> That is, it is the sum of other shorter cycles plus the super cycle:

$$LP\_NT \equiv LP\_SC + LP\_O.$$

Equivalently, in BP filter notation:

$$LP\_BP(2, 70) \equiv LP\_BP(2, 20) + LP\_BP(20, 70).$$

---

<sup>9</sup>Although it is straightforward to decompose our “other shorter cycles” into business cycles (2–8 years) and, say, intermediate cycles (8–20 years), this is not necessary for the study of super cycles, especially given that the various cycles are roughly uncorrelated with each other. See Appendix IV for details.

<sup>10</sup>We initially experimented with three different band-pass specifications for defining super cycles:  $BP(20, 70)$ ,  $BP(20, 50)$ , and  $BP(20, 70)$ . These band-pass windows seem roughly consistent with the duration of super-cycle expansions discussed in Heap (2005, 2007). After some experimentation, we chose  $BP(20, 70)$  as a reasonable characterization of what Heap had in mind. Appendix II shows how the different definitions of super cycle periodicity affect the characterization of the super cycle in the case of copper.

<sup>11</sup>Note that the  $BP(2, 70)$  and  $BP(70, \infty)$  are complements; that is, their sum equals the actual price series.

### III. Empirical Results

Our long-span annual data series on the six LME-traded nonferrous metals from Heap (2005) go back, in some cases, as far as 1850.<sup>12</sup> Real prices are computed using the U.S. CPI (2006 = 100) as the deflator.<sup>13</sup> The ACF filter is applied to the natural logarithm of each real metal price to extract the long-term trend, nontrend and super-cycle components, as defined above.<sup>14</sup> The resulting decompositions are shown graphically below. The following questions are addressed:

- Do the metals prices exhibit any long-term upward or downward trends? Or are they more or less flat, which would be the case if Ongoing depletion of mineral resources was being more or less offset by technological innovations that either reduce the long-run demand for metals and/or turn resources into (economically viable) reserves?
- Is there evidence of a strong super-cycle component for each series? Does its timing more or less match the super-cycle periods identified by Heap: (1) the late 1800s through the early 1900s, (2) the post-WWII period through the early 1970s, and (3) the post-2000 episode, which is still ongoing?
- Are the super-cycle components in the various metals highly correlated, as would be expected if the super cycle is demand driven? That is, is there strong co-movement?
- After accounting for the long-term trends and super cycles, how pronounced are the shorter cycles? Do they indicate considerable price risk at the business and intermediate cycle frequencies that would be relevant for firms undertaking capital investment decisions?

As an illustration, consider the application of the ACF BP filter to the real copper price series (*LRP\_CU*, where R in the series name indicates “real”). The top portion of Figure 1 shows the log of the real copper price series, with the long-term trend superimposed. Note that real copper prices trended downward from 1850 through to the mid-1920s, but remained relatively flat thereafter. It is difficult to argue on the basis of this long-run trend in copper prices that increasing resource scarcity is a dominant concern.

The nontrend component *LRP\_CU\_NT*, which is the difference between the actual series *LRP\_CU* and the long-run trend *LRP\_CU\_T*, is shown in the lower panel of Figure 1. The scaling on the left is in logarithms, so a value

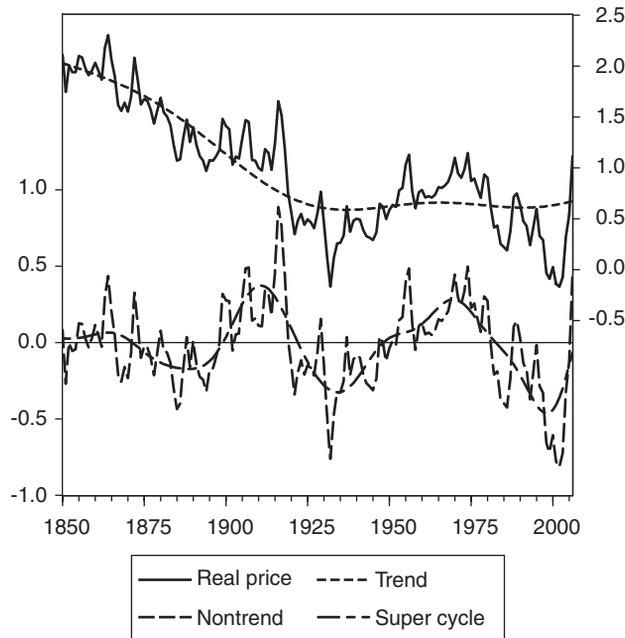
---

<sup>12</sup>Interestingly, the first version of our paper considered only five of the six LME base metals. Tin was overlooked. The later inclusion of tin in the super-cycle dating analysis at the end of the paper had remarkably little effect on our conclusions. Thus, our results are robust in that sense, at least.

<sup>13</sup>Appendix III addresses the choice of deflator.

<sup>14</sup>Tilton (2006) raises the interesting question: when using the ACF filter, how much recharacterization of super cycles and other shorter cycles will occur as more data come in over time? We hope to address this issue in our future research on super cycles.

Figure 1. Real Copper Price Components  
(Log scaling)



Note: This figure shows the decomposition of the log of the real price of copper into its various components using the asymmetric Christiano and Fitzgerald (2003) band-pass filter (denoted BP(.) here.). The long-run trend is defined as the original series minus all cyclical components with periods between 2 and 70 years, as extracted by the BP(2, 70) filter. The (total) nontrend component is just the series that passes through the BP(2, 70) filter, so the trend and nontrend components are complements. The super-cycle component is defined as the cyclical components with periods between 20 and 70 years and is extracted using the BP(20, 70) filter. Note that the super-cycle component is a portion of the total nontrend component, the remainder being cycles with periods between 2 and 20 years. That is,  $BP(2, 70) \equiv BP(2, 20) + BP(20, 70)$ . Both the left- and right-hand axis scalings are in natural logs.

of 0.50 is a 50 percent deviation from the long-term trend. Thus, the cyclical fluctuations from the long-term trend are huge. Recall that a portion of these fluctuations is the super cycle, while the remainder is other shorter cycles. The super-cycle component *LRP\_CU\_SC* is superimposed on the lower panel. The timing of the super-cycle expansions for copper matches up quite well with the dating highlighted in Heap's analysis, although the BP filter analysis dates the beginning of the second super cycle earlier (that is, the mid-1930s rather than post-WWII).<sup>15</sup>

<sup>15</sup>It is interesting to note that the Great Depression actually includes two business cycles according to the NBER dating, with the deep contraction of 1929 being interrupted by a 50-month expansion between March 1933 and May 1937. See [www.nber.org/cycles](http://www.nber.org/cycles).

The extent to which the super-cycle component differs from the total nontrend component in the lower panel reflects the importance of other shorter cycles (such as business and intermediate term cycles). As the lower panel shows, these shorter cycles are substantial. Even if one has confidence about the long-term trend and the super cycle in copper prices, the shorter cycles imply large price risks for those in the industry making long-run investment decisions.

Analogous decompositions for real prices of aluminum (AL), lead (PB), nickel (NI), tin (SN), and zinc (ZN) are shown in Figure 2. Note that the time span covered by the four series differs due to data availability. There is considerable variation in the long-term trends, with aluminum falling steadily over time but nickel falling sharply through the mid-1920s before easing upward thereafter.<sup>16</sup> Like copper, the long-run trend for zinc was relatively flat for most of the post-1920 period, although it seems to have drifted higher in the last 10–15 years of our data sample. Comparing the nontrend component in the lower panels to the superimposed super cycle, it is clear that all price series reflect large cyclical fluctuations above and beyond what is captured by the super cycle.

As the date span differs for the various metal price series shown in Figure 2, it is useful to collect all of the super cycles in Figure 3. There appears to be a general tendency for the super-cycle components to be in a trough in the late 1800s and to rise through the mid-1920s. During the post-WWII period up to about 1975, many but not all of the metal prices are in a strong super-cycle expansion phase. Finally, all of the metals seem to be moving out of a super-cycle trough in the 1990s into a super-cycle expansion, albeit with differences in timing across metals.

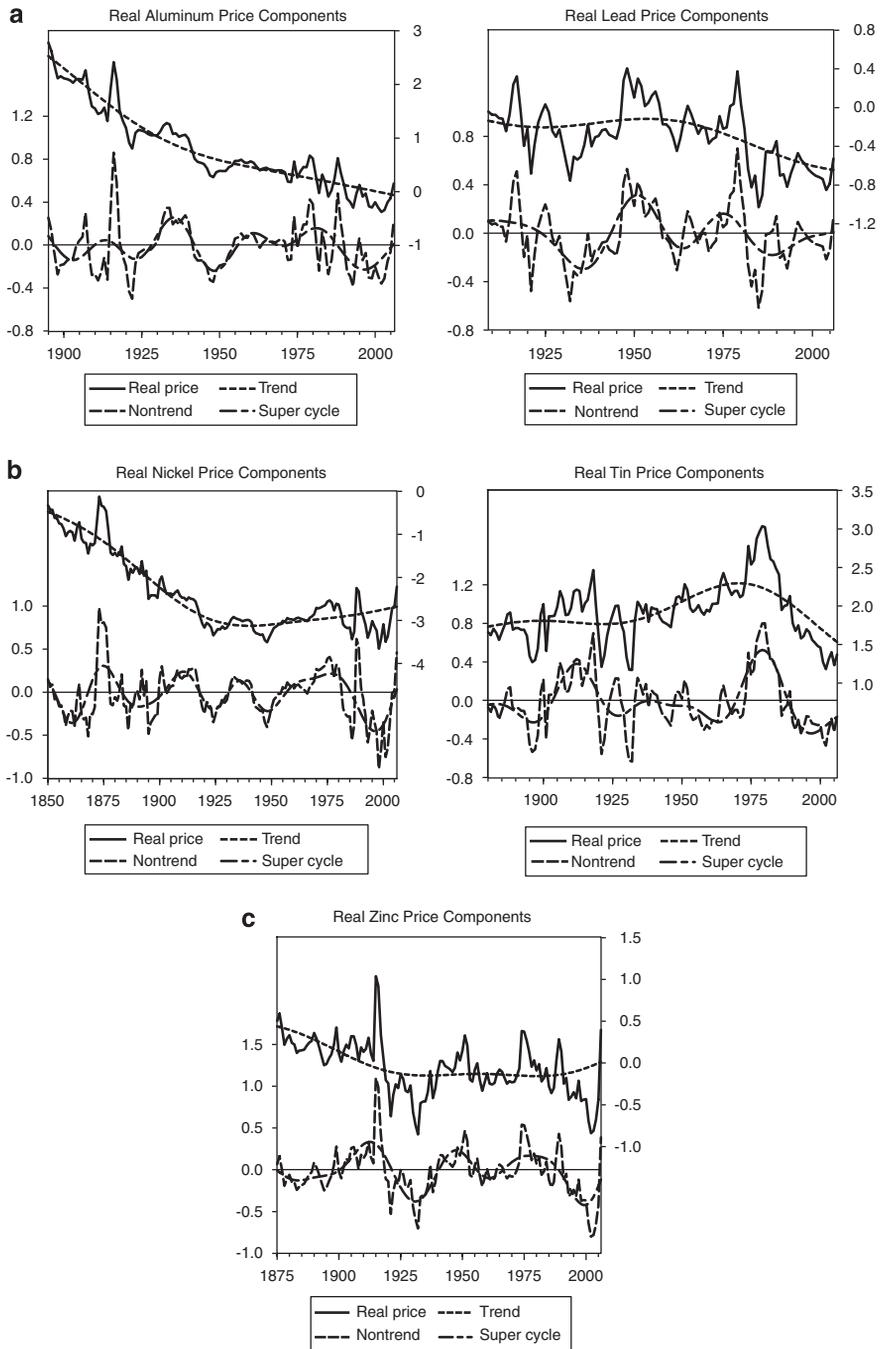
One can summarize the graphical impression that the super cycles of the six metals are highly correlated more formally by examining their correlation matrix and by carrying out principal component analysis. When calculating the correlation matrix among the super-cycle components of the six metal prices, there are a couple of options. One might consider the balanced sample where one includes only the years where all six of the series are available (1909–2006). Alternatively, one could calculate each cell in the correlation matrix using the maximum data span for each pair-wise calculation. The principal component analysis, on the other hand, requires balanced sample.

The correlation results are very similar, so just the balanced sample results (1909–2006) are reported in Table 1. Most of the correlations are highly significant, with the aluminum-copper, aluminum-zinc, and lead-nickel correlations being the exceptions.<sup>17</sup> These correlograms show very little phase differences among the super cycles for the LME6 in that

<sup>16</sup>Our decomposition produces conclusions regarding the nickel price trend that differ from Maxwell (1999, p. 4): “Over the last fifty years as well there has been a downward trend in nickel prices, though price movements in the nickel have been volatile in the short run.”

<sup>17</sup>The interested reader can reference the working paper version of the paper at [www.mines.edu/~jcudding/](http://www.mines.edu/~jcudding/).

Figure 2. (a) Aluminum and Lead Real Price Components, (b) Nickel and Tin Real Price Components, (c) Real Zinc Price Components  
(Log scaling)

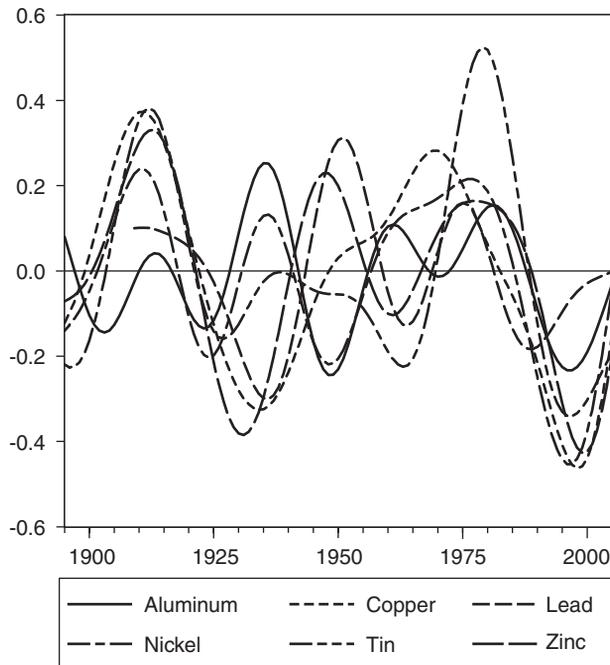


See figure note on following page →

contemporaneous correlations are generally higher than correlations at various leads or lags.

Principal component analysis can be used to assess the importance of unobservable common factors affecting the super-cycle components of the six

Figure 3. Real Super-Cycle Components for LME6  
(Log scaling)



Note: This figure contains super-cycle components for all six LME metals: aluminum (Al), copper (Cu), lead (Pb), nickel (Ni), tin (Sn), and zinc (Zn). In each case, the super-cycle component is obtained by applying the asymmetric Christiano-Fitzgerald BP filter to extract periods between 20 and 70 years from the price series. The left axis is in natural logs and can be interpreted as percentage deviations from the long-term trend.

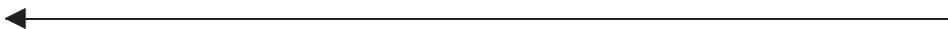


Figure 2. Concluded

Note: This figure shows the decompositions of the log of the real prices of the remaining five LME metals into its various components using the asymmetric Christiano and Fitzgerald (2003) BP filter (denoted BP(.) here.). In each case, the long-run trend is defined as the original series minus all cyclical components with periods between two and 70 years, as extracted by the BP(2, 70) filter. The (total) nontrend component is just the series that passes through the BP(2, 70) filter, so the trend and nontrend components are complements. The super-cycle component is defined as the cyclical components with periods between 20 and 70 years and is extracted using the BP(20, 70) filter. Note that the super-cycle component is a portion of the total nontrend component, the remainder being cycles with periods between 2 and 20 years. That is,  $BP(2, 70) \equiv BP(2, 20) + BP(20, 70)$ . Both the left- and right-hand axis scaling are in natural logs.

Table 1. Correlations: Super-Cycle Components of Real Prices

Correlation	Aluminum	Copper	Lead	Nickel	Tin	Zinc
Aluminum	1.00					
Copper	0.19	1.00				
Lead	-0.47*	0.56*	1.00			
Nickel	0.80*	0.70*	0.03	1.00		
Tin	0.45*	0.58*	0.31*	0.68*	1.00	
Zinc	0.04	0.80*	0.62*	0.49*	0.74*	1.00

Note: Asymptotic standard errors=0.101. This table reports the contemporaneous correlations for the super-cycle components of the six LME metal prices. In each case, the super-cycle component is obtained by applying the asymmetric Christiano-Fitzgerald band-pass filter to extract periods between 20 and 70 years from the price series. The balanced sample 1909–2006 is used. Significance at the 95 percent level is indicated by asterisks, based on the asymptotic standard errors.

metal prices by decomposing their variance-covariance matrix. If all six metals are included, the principal components can only be calculated over the balanced sample from 1909 through 2006. The results are summarized in Table 2.

It is striking that the first principal component (PC1) explains 66 percent of the joint co-variation in the six metal super-cycle components. All six metals have a positive factor loading on the PC1. It seems natural, therefore, to interpret the first principal component obtained from the covariance matrix decomposition of the six metals' super cycles as a summary measure of the super cycle in metals prices. PC1 is shown along with the individual metal super-cycle components in Figure 4. The principal component analysis substantiates the claim that there is a strong positive correlation in the super cycles in the six metal prices.

In an effort to define the super cycle further back in the data sample, the above analysis was repeated using only the three metals whose prices are available from 1875: copper, nickel, and zinc. As Tables 3 and 4 show, the first principal component for these three metals (*PC1\_3*) now explains 78 percent of their joint variation. Figure 5 shows that the timing of the super cycle based on *PC1\_3* matches well (over their common sample) that obtained from the six-metal analysis (denoted *PC1\_6* in Figure 5).

Using the lower panel of Figure 5, one can date the super cycles (using *PC1\_6* when both *PC1\_3* and *PC1\_6* are available). The analysis suggests that the first super-cycle expansion lasted roughly 21 years from 1890 through 1911. The second super-cycle expansion ran from 1930 to 1951, then after a 11-year pause gave rise to a third super cycle from 1962 through 1977 (15 years). Heap's discussion, in contrast, characterizes the post-WWII period through the early 1970s as a single, very long super cycle. The final super cycle began in 1999 and as of 2006 was not yet at the mid-point in its expansion phase. Thus, if we are indeed in a super cycle and the duration of

## SUPER CYCLES IN REAL METALS PRICES?

**Table 2. Principal Components: Super-Cycle Components for Real Metal Prices**

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	0.15	0.11	0.66	0.15	0.66
2	0.05	0.02	0.20	0.20	0.86
3	0.02	0.02	0.10	0.22	0.96
4	0.01	0.00	0.03	0.23	0.98
5	0.00	0.00	0.10	0.23	0.99
6	0.00	0.00	0.00	0.23	1.00

Variable	PC1	PC2
Aluminum	0.12	0.55
Copper	0.54	-0.20
Lead	0.19	-0.52
Nickel	0.39	0.48
Tin	0.52	0.22
Zinc	0.49	-0.33

Note: Eigen values: sum = 0.23; average = 0.04. This table gives results for the principal component analysis for the super-cycle components of the six metal prices over the balanced sample 1909–2006. In each case, the super-cycle component is obtained by applying the asymmetric Christiano-Fitzgerald band-pass filter to extract periods between 20 and 70 years from the price series. According to the top panel in the table, the first principal component PC1 explains 66 percent of the variation in the co-movement of the six metals' super cycles. From the lower panel, one can see that four of the six metals have rather high factor loadings on PC1.

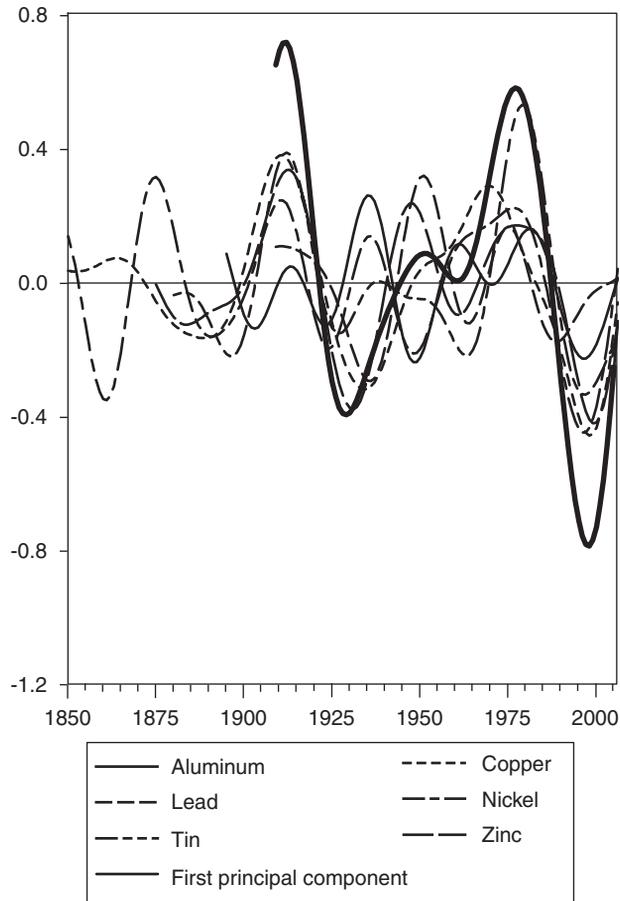
the past three super cycles are any guide, the current cycle may still have some time to run. A cautionary note, however: as we have only identified three past super cycles in the last 150 years or so, it is very difficult to predict their expected duration with any precision.

### IV. Concluding Remarks

The BP filtering technique used in this paper has found considerable evidence of three past super cycles in real metal prices, defined here as cyclical components with expansion phases from 10 to 35 years. The amplitude of the super cycles is large with variations of 20 to 40 percent above and below the long-run trends. Both simple correlations and principal component analysis confirm that the super cycles for six LME metals are highly correlated. The statistical evidence from the BP filter analysis is consistent with the claim by investment industry analysts and industry experts that metal prices entered the early phase of a super cycle at the beginning of the 21st century.

Given our empirical support for the presence of super cycles, the task for future research is to develop formal structural models to explain the sources

Figure 4. Real Super-Cycle Components and First Principal Components  
(Log scaling)



Note: This figure reproduces the super-cycle components for the six LME metal prices along with their first principal component from the principal component analysis reported in Table 2. In each case, the super-cycle component is obtained by applying the asymmetric Christiano-Fitzgerald BP filter to extract periods between 20 and 70 years from the price series. It can be seen that the first principal component is highly correlated with the super-cycle components from the metals. Thus, it can be interpreted as a summary measure of the super cycle for these metal prices taken as a group. Left axis is in natural logs and can be interpreted as percentage deviations from the long-term trend.

or causes of such long cycles. Super-cycle proponents argue that the current super cycle is being caused primarily by Chinese industrialization and urbanization, whereas earlier super cycles were driven by similar developments in the United States, Europe, and Japan. They argue that this development phase is particularly metals intensive. As long as the resulting outward shifts in the demand curves for metals moves metals producers along upward sloping supply curves, higher prices will clearly accompany the sustained surge in metals demand.

SUPER CYCLES IN REAL METALS PRICES?

Table 3. Correlations: Super-Cycle Components of Real Prices

Correlation	Copper	Nickel	Zinc
Copper	1.00		
Nickel	0.65*	1.00	
Zinc	0.81*	0.47*	1.00

Note: Asymptotic standard errors=0.087. This table reports the contemporaneous correlations for the super-cycle components for the three metal prices whose common data sample extends from 1875 to 2006. In each case, the super-cycle component is obtained by applying the asymmetric Christiano-Fitzgerald band-pass filter to extract periods between 20 and 70 years from the price series. Significance at the 95 percent level is indicated by asterisks, based on the asymptotic standard errors.

Table 4. Principal Component Analysis for Copper, Nickel, and Zinc

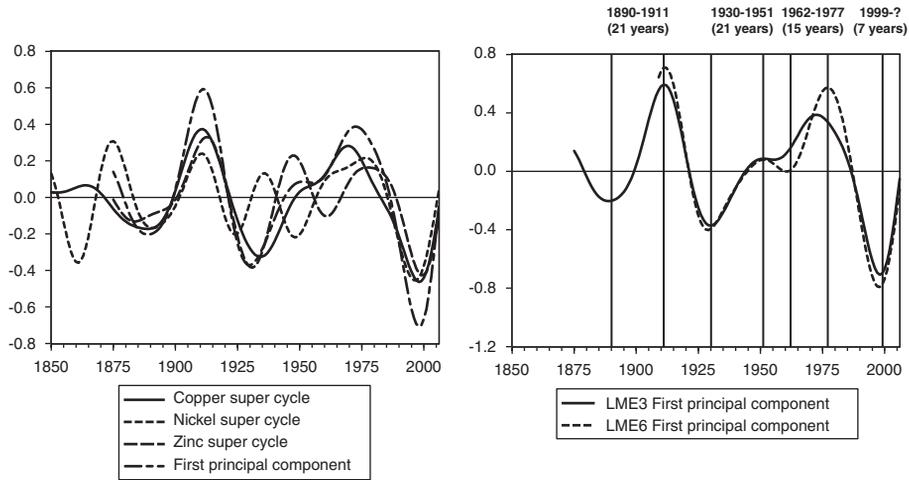
Principal Component Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
PC1	0.09	0.07	0.78	0.09	0.78
PC2	0.02	0.01	0.16	0.11	0.94
PC3	0.01	0.00	0.06	0.12	1.00

Note: Eigen values: sum=0.12; average=0.04. This table contains the principal component analysis for the super cycles in the three longest price series. In each case, the super-cycle component is obtained by applying the asymmetric Christiano-Fitzgerald band-pass filter to extract periods between 20 and 70 years from the price series. It is evident that copper, nickel, and zinc have very strong co-movement. The first principal component (PC1) explains 78 percent of their joint variation.

The sustained demand expansion hypothesis for the super cycle may not be the only one consistent with our results of strong co-movements in real metals prices at the super-cycle frequencies. As mineral economist John Tilton observes, “Another possible explanation, which I prefer given my perceptions of long-run metal supply and demand, is that super cycles are driven by supply: real prices rise when increasing costs due to depletion are greater than falling costs due to new technology, and vice versa. The synchronization of the super cycles for various metals may arise if most new mining technologies (for example, large trucks, bigger shovels, better explosives) reduce the mining costs across a number of metals at more or less the same time.”<sup>18</sup> To the extent that technological improvements are metal specific (for example, the solvent extraction electrowinning (SX-EW) process for copper), however, one would not expect to see high correlation in

<sup>18</sup>Private correspondence with the authors during the fall of 2007 and early winter of 2008.

Figure 5. Comparing LME3 and LME6  
(Log scaling)



Note: The left panel displays the super-cycle components for the three-metal group along with the first principal component from the principal component analysis summarized in Table 4. The right panel puts the first principal components from the three and six metal analyses on the same figure to see if the characterization of the super cycles is similar for the six LME metals taken as a group and the subset of three where the data extend further back in time. The segmentation and the dating above each segmented portion indicate the expansion phase of each super cycle. The six-metal group is used for dating when data for all six metals are available.

super-cycle components across metals. There is also the issue of how long-lasting the impacts of technological changes on metals prices are. Perhaps they are better thought of as inducing intermediate cycles in the 8 to 20-year range, rather than super cycles, although the Comin-Gertler model suggests that endogenous technological innovation waves can produce much long-term cycles in their real business and medium cycle model.

The underlying causes of super cycles cannot be resolved here. Given the current interest in metal price super cycles, however, structural modeling efforts to shed light on the relative importance of various supply and demand-side causes is clearly high on the agenda for future research.

#### APPENDIX I. END USE STATISTICS FOR THE LME METALS

Table A1 shows current global end use consumption of each LME metal used in the analysis in the paper. Although each metal has specific industry end-uses, many of the metals' consumption usages are related in one way or another to construction and transportation activities. End use has, of course, changed over time. For example, tin has gradually replaced lead in soldering applications.

SUPER CYCLES IN REAL METALS PRICES?

Table A1. End Use Consumption for LME6 Metals

	Percent
<b>Aluminum end uses</b>	
Transportation	26
Packaging	22
Construction	22
Machinery	8
Electrical	8
Consumer durables	7
Other	7
Total	100
<b>Copper end uses</b>	
Building	48
Electrical	17
General engineering	16
Light engineering	8
Transportation	7
Other	4
Total	100
<b>Lead end uses</b>	
Batteries	71
Pigments	12
Rolled products	7
Shot/Ammunition	6
Cable sheathing	3
Alloys	1
Total	100
<b>Nickel end uses</b>	
Stainless steel	65
Nonferrous alloys	12
Other alloys	10
Electroplating	8
Other inc. chemicals	5
Total	100
<b>Tin end uses</b>	
Solders	32
Tin plate	27
Other	17
Alloy	14
PC stabilizers	6
Tinning	4
Total	100
<b>Zinc end uses</b>	
Galvanizing	47
Brass and bronze	19
Zinc alloying	14
Chemicals	9

Table A1 (concluded)

	Percent
Zinc semimanufacturing	8
Miscellaneous	3
Total	100

Source: London Metal Exchange (2008).

## APPENDIX II. ELABORATION ON CHOICE OF CUTOFF POINTS FOR VARIOUS CYCLICAL COMPONENTS OBTAINED FROM THE BP FILTER

The BP filter methodology has the advantage that it is possible to decompose a time series into a number of mutually exclusive and exhaustive components. For our purpose, the natural choice revolves around the definition of the super cycle. Initially, we experimented with super-cycle definitions of 20 to 50 years, 30 to 70 years and 20 to 70 years, as these alternatives seemed broadly consistent with the description of super cycles in Heap (2005, 2007).

Figure A1 shows how the three definitions of the super cycle differ when applied to the natural logarithm of the real (CPI-deflated) price of copper.

We ultimately settled on the 20 to 70-year definition of super cycles. With this definition, it makes sense to define the trend to include all cycles with periods above 70 years (denoted  $LP(70, \infty)$ ). We define all cycles with periods between 2 (the minimum detectible cycle period) and 20 years as “other shorter cycles,” denoted  $LP(2, 20)$ . Thus, the log of each real metal price is decomposed into the three components described in the text.

If one is also interested in business-cycle movements in metals prices using the traditional definition of cycles in the 2- to 8-year range, it is straightforward to decompose our shorter cycles into two separate components, business cycles  $LP(2, 8)$  and, say, intermediate cycles  $LP(8, 20)$ :

$$LP = LP(2, 8) + LP(8, 20) + LP(20, 70) + LP(70, \infty).$$

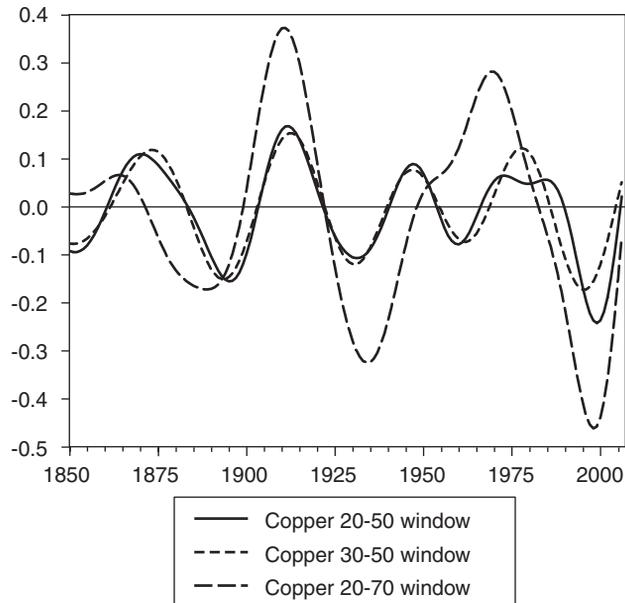
Comin and Gertler (2006) take a similar approach, decomposing various quarterly macroseries into a business cycle component, a medium-term component, and a trend, defined as follows:

$$LY_- = LY(2, 32) + LY(32, 200) + LY(200, \infty).$$

Their medium-term business cycles are defined as the sum of the business cycle (2 to 32 quarters) and medium-term components (32 to 200 quarters).<sup>19</sup> The Comin-Gertler choice of cut-off periods at 200 quarters (that is, 50 years) is somewhat arbitrary, as is our choice of the 20- to 70-year BP window in defining super cycles.

<sup>19</sup>Note that the Comin-Gertler definition of business cycle is atypical in that it includes shorter seasonal and irregular components (with periods from 2 to 8 quarters), rather just the cycles with periods from 8 to 32 quarters as in Baxter and King (1999).

Figure A1. Real Copper Super-Cycle Components. Varying Filter Windows  
(Deflated by CPI)



Note: This figure graphs three possible window specifications for the asymmetric Christiano-Fitzgerald BP filter (BP) used to define super cycles the six LME metals in the paper. The figure shows how the definition of the super cycle for the natural logarithm of the CPI-deflated price of copper is affected by extracting cycles between 20 and 50 years vs. 30 and 70 years, vs. 20 and 70 years. Ultimately, we opted to use the BP(20–70) filter, as it produced super-cycle timing roughly consistent with that proposed by Heap (2005).

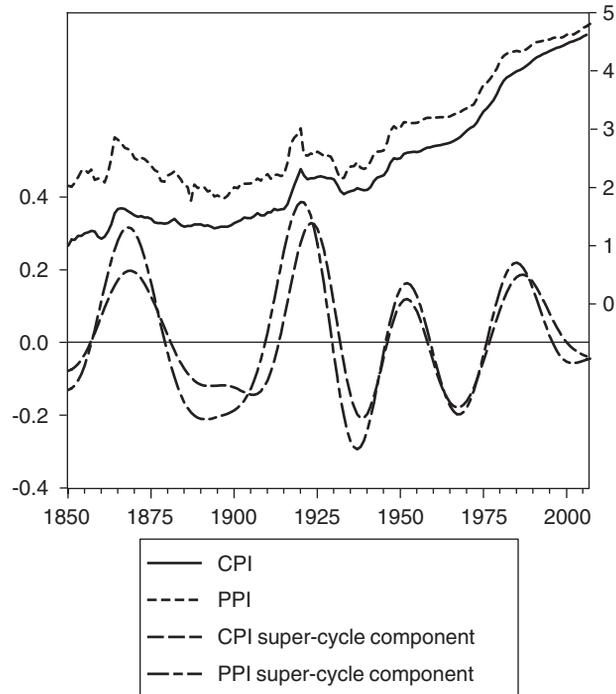
### APPENDIX III. CHOICE OF DEFLATORS: CPI VS. PPI

Discussions of real commodity price behavior invariably raise the question of the “appropriate” deflator (CPI, PPI, MUV, U.S.-based or other). No deflator can make the claim that it is universally “most relevant.” Ultimately, this depends on what relative prices one is most interested in for the questions at hand. For example, suppose a U.S. financial investor is considering investments in commodities (or industrial metals, or precious metals) as an asset class. Presumably she wants to know how their prices move over time relative to the CPI. Percentage changes in the metals prices deflated by the CPI would be the relevant “real” return. Gorton and Rouwenhorst (2004), for example, use the U.S. CPI as their deflator in their analysis of commodities as an asset class.

On the other hand, if one is looking for the price of metal inputs relative to output prices, then one would want to select the particular outputs of interest. Here the PPI for final goods (or particular Subcategories of interest) might be viewed as more relevant, because the PPI includes capital as well as consumption goods and excludes distribution costs and indirect taxes.<sup>20</sup> For a mining company that produces copper using energy

<sup>20</sup>The U.S. Bureau of Labor Statistics website has a nice discussion of the differences in coverage between PPI and CPI: <http://www.bls.gov/ppi/ppicippi.htm>.

Figure A2. Comparing the U.S. CPI and PPI



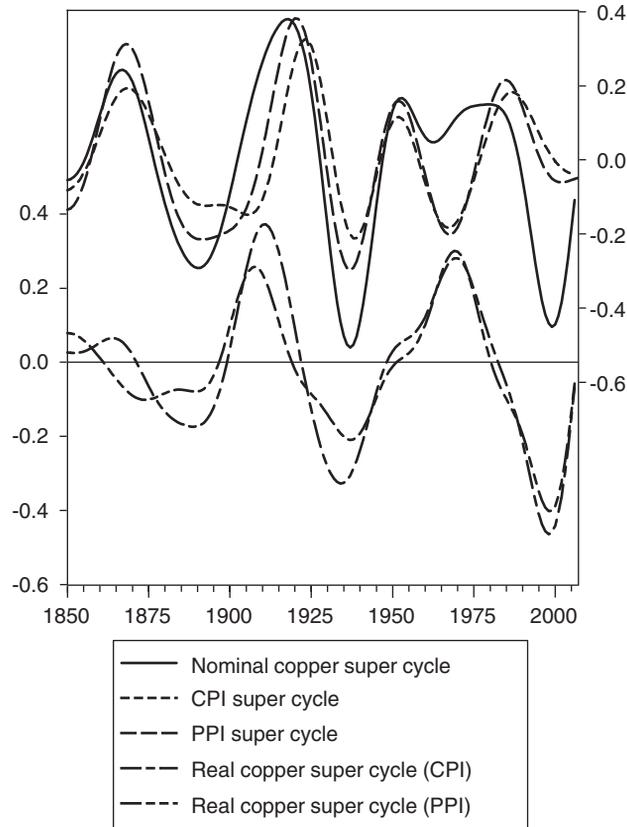
Note: Comparing the CPI and PPI series, it is clear that the CPI has risen more rapidly over the last century and a half than the PPI. Therefore the long-term trend in real commodity prices will be less positive or more negative when the CPI is the chosen deflator. Comparing the super-cycle components of the two deflators, one finds that the PPI super cycle has higher amplitude and generally leads the super-cycle component of the CPI, especially in the first half of the sample. In each case, the super-cycle component was obtained by applying the asymmetric Christiano-Fitzgerald BP filter to extract periods between 20 and 70 years from the price series.

inputs, the relative price of copper in terms of an energy input price index may be especially important to the overall profitability of the operation.

The analysis in the text uses the U.S. CPI from Heap (2005) to deflate nominal metal prices. To illustrate how the choice of deflator might affect our analysis, we consider the alternative of using the U.S. PPI.<sup>21</sup> Figure A2 shows the time plot of the CPI and PPI in log scale (*LCPI* and *LPPI* respectively) in the upper panel and their respective super-cycle components in the lower panel. Comparing the *LCPI* and *LPPI* series, it is clear that the CPI has risen more rapidly over the last century and a half than the PPI. Therefore the long-term trend in real commodity prices will be less positive or more negative when the CPI is the chosen deflator. Figure A3 compares the super-cycle components of the

<sup>21</sup>The long U.S. PPI series for the period 1833 through 2005 was kindly provided by Chris Gilbert. We updated the series through 2006 using the PPI figures from the U.S. Bureau of Labor Statistics (via the Haver USECON database).

Figure A3. Comparison of Copper Super Cycle and Various Deflators



Note: The three series in the upper portion of the figure show the super-cycle components for the logarithm of the nominal prices of copper, the U.S. consumer price index and the U.S. producer price index. The lower portion of this graph shows the resulting super cycles for the (log of the) real copper price depending on which deflator is used. Subtracting the super cycle in the CPI from the nominal copper price's super cycle yields the super cycle for the CPI-deflated price of copper. Analogously, subtracting the super cycle in the PPI from the nominal copper price's super cycle yields the super cycle for the PPI-deflated price of copper. Because the super-cycle component of the PPI leads the CPI, especially during the early years of the sample, the use of the PPI rather than the CPI as deflator would shift the copper super cycle forward in time. In particular, note how the first super-cycle expansion in the later 1800s and early 1900s is shifted forward in time and is lower in amplitude when the PPI is chosen as the deflator.

two deflators (*LCPI\_SC* and *LPPI\_SC*), one finds that the PPI super cycle has higher amplitude and generally leads the super-cycle component of the CPI, especially in the first half of the sample.<sup>22</sup>

The choice of deflator can have a potentially large impact on the characterization of super cycles in real metals prices. The logarithm of the real price of copper used in the text

<sup>22</sup>An article on the BLS website contains a discussion of lead lag relationships between the PPI and the CPI: <http://www.bls.gov/opub/mlr/2002/11/art1full.pdf>.

is, of course, just the log of the nominal price minus the log of the CPI. Interestingly, this identity continues to hold when examining super-cycle components (as the BP filter is a linear operator):

$$LRP\_CU\_SC \equiv LP\_CU\_SC - LCPI\_SC.$$

## REFERENCES

- Adelman, I., 1965, "Long Cycles: Fact or Artifact?" *The American Economic Review*, Vol. 55, No. 3, pp. 444–63.
- Armstrong, C., O. Chaundry, and S. Streifel, 2006, "The Outlook for Metals Markets," paper presented at the G-20 Deputies Meeting, Sydney, Australia.
- Baxter, M., and R.G. King, 1999, "Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time Series," *The Review of Economics and Statistics*, Vol. 81, No. 4, pp. 575–93.
- Blanchard, O., 1997, "The Medium Run," *Brookings Papers on Economic Activity*, No. 2, pp. 89–158.
- Cashin, P., and J. McDermott, 2002, "The Long-Run Behavior of Commodity Prices: Small Trends and Big Variability," *IMF Staff Papers*, Vol. 49, No. 2, pp. 1–26.
- Christiano, L., and T. Fitzgerald, 2003, "The Band Pass Filter," *International Economic Review*, Vol. 44, No. 2, pp. 435–65.
- Cogley, T., and J.M. Nason, 1995, "Effects of the Hodrick-Prescott Filter on Trend and Difference Stationary Time Series Implications for Business Cycle Research," *Journal of Economic Dynamics and Control*, Vol. 19, No. 1–2, pp. 253–78.
- Comin, D., and M. Gertler, 2006, "Medium-Term Business Cycles," *The American Economic Review*, Vol. 96, No. 3, pp. 523–51.
- Cuddington, J.T., and C.M. Urzúa, 1989, "Trends and Cycles in the Net Barter Terms of Trade: A New Approach," *The Economic Journal*, Vol. 99, No. 396, pp. 426–42.
- , R. Ludema, and S.A. Jayasuriya, 2007, "Prebisch-Singer Redux," in *Natural Resources: Neither Curse nor Destiny*, ed. by D. Lederman and W.F. Maloney (Stanford, California, Stanford University Press).
- Davis, G., and M. Samis, 2006, "Using Real Options to Manage and Value Exploration," *Society of Economic Geologists Special Publication*, Vol. 12, No. 14, pp. 273–94.
- Deaton, A., and R. Miller, 1995, "International Commodity Prices, Macroeconomic Performance, and Politics in Sub-Saharan Africa," *Princeton Essays in International Finance*, No. 79.
- Evans, G.W., S. Honkapohja, and P. Romer, 1998, "Growth Cycles," *The American Economic Review*, Vol. 88, No. 3, pp. 495–15.
- Gilbert, C.L., 2007, "Metals Price Cycles," paper presented at the Minerals Economics and Management Society, Golden, Colorado, April 17.
- Gorton, G., and K.G. Rouwenhorst, 2004, "Facts and Fantasies about Commodity Futures," *Financial Analysts Journal*, Vol. 62, No. 2, pp. 47–68.
- Heap, A., 2005, *China—The Engine of a Commodities Super Cycle* (New York, Citigroup Smith Barney).

- , 2007, “The Commodities Super Cycle & Implications for Long Term Prices,” paper presented at the 16th Annual Mineral Economics and Management Society, Golden, Colorado, April.
- Howrey, E.P., 1968, “A Spectrum Analysis of the Long-Swing Hypothesis,” *International Economic Review*, Vol. 9, No. 2, pp. 228–52.
- Jerrett, D., and J.T. Cuddington, 2008, “Broadening the Statistical Search for Metal Price Super Cycles to Steel and Related Metals,” *Resources Policy*, Vol. 33, No. 4 (forthcoming).
- Labys, W.C., A. Achouch, and M. Terraza, 1999, “Metal Prices and the Business Cycle,” *Resources Policy*, Vol. 25, No. 4, pp. 229–38.
- London Metal Exchange, 2008, “Non-Ferrous Metals,” London Metal Exchange (March 10). Available on the Internet: [lme.com/non-ferrous.asp](http://lme.com/non-ferrous.asp).
- Maxwell, P., 1999, “The Coming Nickel Shakeout,” *Minerals and Energy*, Vol. 14, pp. 4–14.
- McDermott, J.C., P.A. Cashin, and A. Scott, 1999, “The Myth of Co-Moving Commodity Prices,” Bank of New Zealand Discussion Paper G99/9, Wellington, New Zealand.
- Morgan Stanley, 2006, *Global Commodities Review* (New York, Morgan Stanley).
- Nelson, C.R., and H. Kang, 1981, “Spurious Periodicity in Inappropriately Detrended Time Series,” *Econometrica*, Vol. 49, No. 3, pp. 741–51.
- Pindyck, R.S., and J.J. Rotemberg, 1990, “The Excess Co-Movement of Commodity Prices,” *The Economic Journal*, Vol. 100, pp. 1173–89.
- Radetzki, M., 2006, “The Anatomy of Three Commodity Booms,” *Resources Policy*, Vol. 31, No. 1, pp. 56–64.
- , 2008, *A Handbook of Primary Commodities in the Global Economy* (Cambridge, Cambridge University Press).
- Rogers, J., 2004, *Hot Commodities: How Anyone Can Invest and Profitably in the World's Best Market* (New York, Random House).
- Sillitoe, R.H., 1995, “Exploration and Discovery of Base- and Precious-Metal Deposits in the Circum-Pacific Region During the Last 25 Years,” *Resource Geology Special Issue*, Vol. 19, p. 119.
- Solow, R., 2000, “Toward a Macroeconomics of the Medium Run,” *Journal of Economic Perspectives*, Vol. 14, No. 1, pp. 151–8.
- Tilton, J.E., 2006, “Outlook for Copper Prices—Up or Down?,” Paper presented at the Commodities Research Unit World Copper Conference. Santiago, Chile, April.
- , and G. Lagos, 2007, “Assessing The Long-Run Availability of Copper,” *Resources Policy*, Vol. 32, No. 1–2, pp. 19–23.